# Learning From Multiple Representations: Roles of Task Interventions and Individual Differences

**Jennifer G. Cromley**

**Department of Educational Psychology, College of Education, University of Illinois at Urbana-Champaign**

Produced with funding from the US National Science Foundation award #1661231. Opinions are the author's own and do not reflect the policies of the National Science Foundation or the US Government.

**Jennifer Cromley** is professor of Educational Psychology at the University of Illinois at Urbana-Champaign. Her research concerns comprehension of illustrated scientific text and cognitive and motivational predictors of retention in Science, Technology, Engineering, and Mathematics majors. She has conducted basic and applied classroom intervention research in both areas, including fostering student comprehension of diagrams at the middle school and high school level, as well as research on the strategy of drawing-to-learn.

Abstract: Learning from multiple representations (MRs) is not an easy task for most people, despite how easy it is for experts. Different combinations of representations (e.g., text + photograph, graph + formula, map + diagram) pose different challenges for learners, but across the literature researchers find these to be challenging learning tasks. Each representation typically includes some unique information, as well as some information shared with the other representation(s). Finding one piece of information is only somewhat challenging, but linking information across representations—and especially making inferences—are very challenging and important parts of using multiple representations for learning. Coordination of multiple representations skills are rarely taught in classrooms, despite the fact that learners are frequently tested on them. Learning from MRs depends on the specific learning tasks posed, learner characteristics, the specifics of which representation(s) are used, and the design of each representation. These various factors act separately and in combination (which can be compensatory, additive, or interactive). Learning tasks can be differentially effective depending on learner characteristics, especially prior knowledge, self-regulation, and age/grade. Learning tasks should be designed keeping this differential effectiveness in mind, and researchers should test for such interactions.

Keywords: Individual differences; Learning task x Individual difference interactions

## Introduction

Learning from multiple representations (MRs)—combinations of text, diagrams, tables, animations, graphs, formulas, maps, and other representations of information—is not an easy task for most people, despite how easy it is for experts. Different combinations of representations (e.g., text + photograph, graph + formula, map + diagram) pose different challenges for learners, but across the literature researchers find these to be challenging learning tasks. Each representation typically includes some unique information, as well as some information shared with the other representation(s). For example, in Figure 1 showing the anatomy of bones in the inner ear, the text explains that the eardrum would be found to the left of the malleus (hammer) bone shown in the diagram. The diagram shows that there are two joints among these three bones, and names the joints. Both text and diagram refer to all three bones, and also refer to the incus (anvil) as coming between the malleus (hammer) and stapes (anvil) bones.

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In these types of multi-representational information sources, finding one piece of information is only somewhat challenging, but linking information across representations is a very challenging and important part of using multiple representations for learning. For example, linking information across text and diagram (often called coordinating multiple representations or

CMR) such as finding only one of the bones in the diagram is a relatively simple task (White, Chen, & Forsyth, 2010). A more challenging CMR task is using the information from the representations to draw conclusions or inferences; for example, a disease called otosclerosis involves extra bone growing at the base of the stapes. Understanding why this would cause hearing loss requires drawing a number of conclusions—the bones transmit sound between the eardrum and the inner ear, and the base of the stapes touches the inner ear, so extra bone could interfere with transmitting sound, which could cause hearing loss. The information in this case is provided in the MRs, but the reader needs to actively make inferences (draw conclusions) from the information provided. Even the straightforward fact that the three bones are linked into a chain, and that the chain transmits sound, is not stated explicitly in this multi-representational text, and is an inference that the reader needs to make. The distinction between learning facts and making inferences from MRs is important, as supporting learners to engage in CMR sometimes requires different supportive or instructional methods for various types of learning outcomes.

Learning from multiple representations does not only depend on the learner actively searching or making inferences. Learning from multiple representations depends on a number of different factors, all of which are in play simultaneously:

- Learner characteristics—the focus of this chapter: Does the learner already have some knowledge of the topic, vocabulary knowledge (word meanings), or well-developed reading comprehension? Higher or lower spatial skills (such as mentally rotating a 3D shape in space), working memory (holding information in memory while solving a problem), or a learning disability? Motivation to learn about the topic (such as a person just diagnosed with otosclerosis)? Knowledge of specific symbols or conventions (e.g., color keys used in maps)? Other individual differences?

- Which representations are used: Maps and graphs use very specific conventions (e.g., compass rose, contour lines, X and Y axes), whereas photographs can be extremely varied. Static diagrams can be investigated at length, but animation or video goes by very quickly. Some diagrams are extremely formalized (e.g., free body diagrams in physics), whereas others are not.
- Design features of each representation: Both text and visuals can be made more comprehensible by changing the design. Headings can be bolded, words and visuals can be linked with lettering, numbering, color, highlighting, or animated cues/signals. Less-important parts of visuals can be made less prominent (e.g., not brightly colored). Distracting—albeit interesting—features can be removed. Speed controls can be provided for videos or other learning environments.
- What learning tasks are assigned:[1] The same set of multiple representations can be perceived as easy for certain learning tasks assigned to learners, but could be perceived as quite challenging for other tasks, as suggested by the find-a-bone vs. infer-a-cause tasks in the example above. Does the assignment require using a particular learning strategy, such as copying or making a diagram or using a hands-on model? Are students instructed in how to coordinate MRs? Do the tasks require finding an answer (receptive) or creating something new (productive)? We use the term *task intervention* to refer to a

[1] We mean *task* in the same broad sense that it was used by Snow et al. (2000) in the Report of the National Reading Panel—all of the instructions and activities that surround a particular instance of reading, separate from the characteristics of the text characteristics and reader characteristics.

change in the tasks that learners carry out when learning from multi-modal materials. These range from full-scale strategy instruction programs to prompting of a single learning strategy, during-learning tasks such as interspersed fill-in-the blank activities, or directing learners to replay video or conduct multiple simulation trials.

In summary, learning from multiple representations depends on the specific learning tasks posed, learner characteristics, the specifics of which representation(s) are used, and the design of each representation. To make matters more complicated, these various factors can act separately and in combination, so that in some cases only learner spatial skills are in play, but sometimes required strategies (such as making a drawing to learn from the multiple representations) work better for high-spatial learners and worse for low-spatial learners, or vice versa.

When different learner, learning material, and/or learning task factors act in combination, we can think of them as being compensatory, additive, or interactive. *Compensatory* processes would be ones where a strength in one factor can compensate for a weakness on another factor. For example, Höffler and Leutner (2011) wrote about high spatial skills (strong on a learner characteristic) as compensating for poor multimedia design (weak on a design factor). *Additive* processes would be ones where a strength in one factor and a strength in another factor would yield better learning, exactly and only to the extent that one would expect by adding the effects of each. For example, Olympiou and Zacharia (2012) compared learning from a computer-simulated learner-controlled optics laboratory session versus a hands-on laboratory session versus a combination of computer-simulated and hands-on sessions. Learners' prior knowledge about optics was also collected. On a conceptual light and color test, the combined condition resulted in higher scores, and students who began the study with more topic knowledge had higher scores: participants' scores were the result of adding the benefits that one would expect from their experimental condition and the benefits that one would expect from their level of prior knowledge. *Interactive* processes would be ones where a strength in one factor and a strength on another factor yield results greater than what would be expected by simply adding the effects of each (interaction is sometimes called moderation, in the sense that how strong the effect of A on B depends on one's score on C, and C is called the moderator variable).

For example, in a computer-based simulation for learning about electrical circuits (Johnson, Ozogul, & Reisslein, 2015), students who were in a condition where relevant parts of a graph were pointed out with a signal (sometimes called a cue) scored higher on circuit problems than those in a condition without signals; students who had higher prior knowledge also scored higher on circuit problems. Combinations of signaling and prior knowledge had even stronger effects; students who were in the signals condition but started the study with low prior knowledge had much higher scores on circuit problems than those in the no-signals condition, thus closing the achievement gap between low- and high-prior-knowledge learners. There was an interaction between condition and prior knowledge, in that effect of condition depended on level of prior knowledge (condition actually did not make a difference for the high prior knowledge participants), and effect of prior knowledge depended on condition (low prior knowledge students benefited from the signaling condition, but high prior knowledge students scored the same regardless of condition). Interactions can be thought of as multiplying—not just adding—the effect of each factor, such as the prior knowledge x design interaction above.

The experiments above are samples from a wide range of methods that have been developed and tested to teach CMR skills. These methods of CMR instruction can be quite effective, depending on which representations are used (a task x representation interaction). Ironically, these CMR skills are rarely taught in actual classrooms, even though CMR skills are frequently tested in end-of-course tests, national and international assessments, and standardized achievement tests (LaDue, Libarkin , & Thomas, 2015).

**Review of the Literature**

I focus in this chapter on how individual differences play a role in learning from multiple representations, from a systematic search for peer-reviewed articles on learning in science, math, and engineering published 2005-2016. In order to understand how individual differences and learning task x individual difference interactions might vary depending on the learning outcome measured, we[2] categorized dependent variables in the studies as

- Factual: tests that require recall or recognition of a single piece of information,
- Inferential: tests that require combining provided pieces of information, sometimes called comprehension by authors of the studies we reviewed,
- Procedural: tests that require remembering the order of problem-solving steps, or
- Transfer: tests that require applying learned skills and information to a new context.

We focused our review on comparisons of different conditions using the same multimedia (e.g., hypermedia with tutoring vs. hypermedia without tutoring). Despite the importance of comparing multimedia to regular instruction, it is difficult to determine in those

[2] I am indebted to LuEttaMae Lawrence for her work locating, coding, and entering data from articles on this project.

studies whether differences are due to the medium or to the specific characteristics of the multimedia (e.g., is it the tutoring or the hypermedia that makes the difference?).

**Individual differences.** As a basis for design principles, theories of multimedia learning most strongly emphasize background knowledge and working memory as individual differences that may affect learning. As with reading comprehension, background knowledge should aid in comprehending MRs, and knowledge is known to affect perceptual processes—learners who know more actually perceive differently (Shah & Freedman, 2011). The limited capacity of working memory is posited to be an important obstacle to learning in both Cognitive Load Theory (Paas & Sweller, 2014) and the Cognitive Theory of Multimedia Learning (Mayer, 2014), in the sense that learners can easily feel overwhelmed by the amount of information in MRs. In addition, developmental and cognitive psychologists who study spatial skills have emphasized the role of such skills in using visual representations (Kastens, Pistolesi, & Passow, 2014).

Many other individual differences have been studied in the multiple representations literature, including intelligence; logic skills; general academic ability; science, reading or math scores; self-regulated learning; effort; sex; affect/mood; and various motivational variables (e.g., interest, need for cognition).

Direct effects of individual differences on learning suggest that a particular individual characteristic matters for factual learning, for drawing inferences from what was learned, or for transfer of learning to new situations or domains. If working memory is important for inferential learning, then there should be a significant correlation between scores on a working memory measure and scores on an inference measure given after learning from text+diagrams (e.g., Isberner et al., 2013; $r$ = .34,). In our literature review, we categorized correlations between individual differences and learning into ones that involve prior knowledge measures, motivational variables, reading comprehension, reasoning, spatial skills, working memory, and other. The number of studies reporting correlations, together with the number of effects, for each type of learning outcome is shown in Table 1.

Table 1

*Number of Studies and Effects for Each Individual Difference Type and Learning Outcome*

| Individual difference | Factual Outcome (number of studies/ number of effects) | Inferential Outcome (number of studies/ number of effects) | Transfer Outcome (number of studies/ number of effects) |
|---|---|---|---|
| Prior knowledge | 5/11 | 0/0 | 4/4 |
| Motivational variables | 4/8 | 1/2 | 2/2 |
| Reading comprehension | 2/5 | 0/0 | 2/2 |
| Deductive reasoning | 2/5 | 2/8 | 0/0 |
| Spatial skills | 4/12 | 2/2 | 2/5 |
| Working memory | 2/6 | 1/1 | 0/0 |
| Other | 3/5 | 4/11 | 1/6 |

***Prior knowledge.*** Prior knowledge has a mean correlation of $r$ = .42 with factual outcomes from learning with multimedia and a mean correlation of $r$ = .37 with transfer outcomes from learning with multimedia. These results were positive for learning about chemistry, biology, ecosystems, and machinery (pulley systems and flushing cistern). They held for middle school, high school, and undergraduate students. As with learning from text alone, a student's prior knowledge contributes to learning from animations, simulations, and text + diagrams. For factual learning, this is consistent with many different learning theories, as the learner with more existing topic-relevant information in memory can more easily connect the newly-presented information to information in memory (an encoding advantage). For transfer of learning, this is consistent with models of analogical transfer, as the existing knowledge becomes a scaffold for an integrated mental model that is then mapped onto the novel (transfer) situation. It should be noted that a very large number of other studies measured prior knowledge, but did not report a correlation with learning outcomes (most often, groups were compared on pretest prior knowledge).

***Motivational variables.*** Across a range of different motivational variables, motivation has a mean correlation of $r$ = .11 with factual outcomes from learning with multimedia, a mean correlation of $r$ = .36 with inferential outcomes, and a mean correlation of $r$ = .25 for transfer. Although it is odd to combine results using different motivational variables, there are not enough studies using any one variable to analyze the main motivational constructs separately. The results for factual outcomes come from hypermedia, text + diagrams, and games; are predominantly with middle school students; and range from interest to mastery goals, self-concept, and entity self-beliefs about learning. The small effect is not surprising, as factual learning requires relatively low effort, so motivation would not be expected to have a large effect. By contrast, the more effortful inferential outcomes show a larger effect, though both come from the same study (Merchant et al., 2012) using virtual reality. The two transfer effects both come from text + diagram research. Perhaps the lower effect on transfer is due to the cognitive demands of transfer, which cannot be overcome simply with increased motivation.

***Reading comprehension.*** Comprehension of text would be expected to assist multimedia learning for at least two reasons: 1) it reflects general linguistic comprehension (whether print or spoken) and 2) it should boost comprehension of print text in multimedia that use print. Consistent with this expectation, reading comprehension has a mean correlation of $r = .44$ with factual outcomes from learning with multimedia and a mean correlation of $r = .49$ with transfer outcomes from learning with multimedia. It should be noted that all of these effects come from the same research team, and all are from middle school students learning from text + diagrams.

***Deductive reasoning.*** As with reading comprehension, there may be different reasons why deductive reasoning relates to learning from multimedia: 1) it may reflect a general intelligence factor (g) which would be expected to correlate with all types of learning outcomes, and 2) it uses the same skill tested in inferential learning measures from multimedia. As with all texts, the authors of multimedia do not make every relation explicit in the learning materials, and learners who can accurately draw their own conclusions are benefited by having such deductive reasoning skills. Consistent with this expectation, deductive reasoning has a mean correlation of $r = .42$ with factual outcomes from learning with multimedia and a mean correlation of $r = .41$ with inferential outcomes from learning with multimedia. Even if specific during-learning inferences are not remembered at post-test, the declarative knowledge that went into those inferences might be remembered better, explaining the effects on factual learning from multimedia. These findings about deductive reasoning come from two studies, one on a simulation of machine operation and one on an animation of the cardiovascular system.

***Spatial skills.*** From a theoretical perspective, multimedia may be advantageous over text because visuals preserve the spatial relations among parts, and these spatial relations are hard to capture in words. This implies that learners' spatial skills may affect their learning from multimedia. However, competing hypotheses have been put forward—some have argued that low-spatial students need the visuals because they explicitly show spatial relations, whereas others have argued that visuals are better understood by high-spatial students. Published correlations strongly support the latter position—spatial skills correlate positively with learning from multimedia. The mean correlations are $r$ = .25 with factual outcomes from learning with multimedia, a mean correlation of $r$ = .40 with inferential outcomes, and a mean correlation of $r$ = .20 for transfer. The research uses high school and undergraduate samples, mostly learning biology topics.

Factual measures often ask for information about one specific part or element named in the multimedia presentation, such as a definition. Inferences, by contrast, may require using spatial information such as blood entering the left atrium, being squeezed down through the mitral valve, and entering the left ventricle below. This could explain the larger relation of spatial skills to multimedia learning for inferential outcomes. As with motivation, perhaps the lower effect on transfer is due to the cognitive demands of transfer, which cannot be overcome simply with better spatial skills. It should be noted that thousands of spatial skills tests exist, which map onto dozens of spatial skills typologies. The most commonly used spatial tests in the multimedia literature are the Mental Rotations Test and various hidden figures/embedded figures tests. Different multimedia learning tasks might tap these skills differently—understanding steoreoisomers in organic chemistry draws strongly on rotation, whereas understanding a weather map requires distinguishing specific information within a complex 2-D map.

***Working memory.*** Theories of multimedia rely strongly on the limited capacity assumption from models of memory. Despite the theoretical centrality of working memory, studies have rarely measured learners' WM. Two studies of undergraduates, one on learning plant biology with hypermedia and one on learning about tectonic plates with animation, show a mean correlation of $r$ = .28 with factual outcomes. Low working memory capacity does indeed seem to interfere with factual learning from hypermedia and animation.

***Other individual differences.*** Five correlations of other individual differences (SRL, paraphrasing, monitoring, satisfaction with learning materials, and game usability) were found for factual outcomes, eleven correlations (paraphrasing, monitoring, verbal ability, perceived ease of use, knowledge of visualization conventions) with inferential outcomes, and six correlations (reaction time on a dual task, lesson difficult rating, and self-reported mental effort) for transfer outcomes. The correlations for monitoring and paraphrasing are negative (i.e., monitoring indicates lapses in comprehension), and of the 22 correlations, 14 are small (< .20).

In summary, direct effects of individual differences on learning are most often significant for prior knowledge (more knowledgeable learners gain more from MRs), reading comprehension (those better at reading comprehension gain more from MRs), and reasoning. Direct effects of these variables on learning are mixed for spatial skills, and small for motivation and 'other' individual differences. There are large literatures on pre-teaching to build knowledge, reading comprehension instruction, and methods for teaching reasoning; all of these individual differences can be strengthened with the aim of later improving learning from multimedia.

**Task intervention x Individual differences interactions.** Putting together what we know about task interventions and individual differences, some task modifications might be more beneficial for students with certain individual characteristics. A strong prediction of Cognitive Load Theory (CLT) is that design features meant to help low-knowledge learners might not help—or might even harm—high-knowledge learners (called the expertise reversal effect). For example, could cues or signaling help low-knowledge learners but not make a difference to high-knowledge learners? We can generalize this beyond just the multimedia design features and knowledge that are the focus of CLT, to ask about task interventions and any individual differences, such as drawing helping high-spatial learners but harming low-spatial learners.

Across 27 task x individual difference interactions tested in articles in this literature review, we found that prior knowledge, self-regulated learning, mastery-approach goal orientation (motivation), and age/grade in school reliably interacted with task manipulations (see detailed descriptions of 10 significant interactions below). Reading skills sometimes did, and rarely were there interactions with learner sex, interest, need for cognition, mental effort, or reasoning. One way of thinking about these interactions is in terms of closing known achievement gaps (e.g., between males and females or high-achieving and low-achieving students; expertise reversal) vs. worsening these known achievement gaps (i.e., benefiting those who are already at an advantage). That is, in some of the interactions we found, the intervention was more helpful to a traditionally lower-performing group such as females in math; thus, the intervention helped to close the male-female achievement gap. In other interactions we found, the intervention was actually more helpful to the group that was already performing better such as high-prior-achievement students; thus, the intervention helped to make the achievement gap worse than it had been before the study.

**Knowledge interactions.** Bodemer and Faust (2006) tested different computer-based text-and-diagram conditions for fostering CMR on a science topic (operation of a heat pump) with undergraduates. They found that drag-and-drop conditions benefited high-knowledge learners more than low-knowledge learners. Bokosmaty, Sweller, and Kalyuga (2014) compared different amounts of guidance for solving geometry problems using a computer-based text-and-diagram learning environment for 8$^{th}$ and 9$^{th}$ grade students. They found that less-elaborate instructional conditions (modeling solution steps *or* explaining which theorems supported the appropriate step, but not both) benefited high-knowledge learners more.

**Skill-level interactions.** Pachman, Sweller, and Kalyuga (2013) compared customized geometry problem assignments vs. free choice of geometry problem assignments using paper and pencil text-and-diagram learning for eighth grade students. They found that allowing students free choice of which problems to practice—rather than focusing on weak areas—benefited lower-skilled students more, but made little difference for high-skilled students. Pachman, Sweller, and Kalyuga (2014) similarly tested customized and free choice geometry work for eighth grade students. They similarly found that focusing practice mostly on weak areas—rather than practicing all skills from a chapter—benefited higher-skilled students more, but made little difference for low-skilled students.

**Age interaction.** Mason and Tornatora (2016) tested instruction to compare-and-contrast, versus no instructions to compare, or sequential text-and-diagrams with 5$^{th}$ and 7$^{th}$

grade students learning about heat flow and states of matter. They found that 7th grade students benefited more from comparing-and-contrasting instructions than did younger students.

**Sex interaction.** DeLeeuw and Mayer (2011) found that fostering competitive play in an educational game about electrical flow through circuits helped level the playing field for female undergraduate players; when there were no messages fostering competition, females under-performed males.

**Motivational interactions.** Yaman, Nerdel, and Bayrhuber (2008) found that worked examples showed extra benefits for high school students learning about cellular respiration from a simulation for high-interest students. Duffy and Azevedo (2015) found that a hypermedia-based intelligent tutoring intervention on the circulatory system was more beneficial for undergraduate students focused on getting a higher grade than others, and led to lower scores for those focused on learning for understanding.

**Reading comprehension interaction.** Mason, Pluchino, and Tornatora (2015) tested effects of eye movement modeling (EMME) for seventh-grade students learning about aquatic food chains from text and diagrams. They found that students with lower reading comprehension were benefited by eye movement guidance (showing them where and in what sequence to look at the page), whereas high comprehenders were not affected by EMME.

**Self-regulated learning interaction.** Wang (2011) compared learning from animations about evolution using a peer recommendation system (fellow students recommend a learning resource vs. no peer recommendation system) for seventh grade students. Wang found that peer-recommended argumentation leveled the playing field for low-SRL students, compared to the control condition which was significantly better for high-SRL students.

Of these 10 significant interactions, 5 made achievement gaps worse by benefiting already-advantaged students more (higher knowledge, skill, interest, or age), 4 closed achievement gaps by benefiting disadvantaged students more (lower skill, reading comprehension, SRL, or females), and one was neutral. Thus, testing task x individual difference interactions per se does not lead overwhelmingly to closing achievement gaps.

We can think about these task x individual difference interactions in a few ways: 1) Some task interventions perhaps should only be used with a specific subset of learners: For example, if drawing-to-learn disadvantages low-spatial learners, it should only be targeted to high-spatial students. Alternatively, 2) Some task modifications are inequitable, and perhaps should not be used if an equitable task modification exists: If verbally completing a partial diagram works as well on average but does not disadvantage a subgroup of students, then verbal completion should be chosen over visual completion. 3) In cases where a task intervention appears to not help learning, this could be because it was effective for a subgroup of learners (in an individual difference that was not tested) and ineffective for another subgroup of learners. In other words, when interactions are not tested, a non-significant main effect can hide a significant interaction. What to do about these three interpretations might depend on a number of factors, including whether the individual difference is easy enough to measure, whether data on the individual differences is readily available (prior reading achievement probably is, spatial skills probably are not), the makeup of a class (if all high-spatial, there is no issue), and the availability of other task modifications (with these MRs on students at this age).

**New Insights and Future Directions**

The nuanced pattern of results above, and the range of task intervention types, strongly suggests that coordinating MRs is not one "thing," it varies by representations and representation combinations, each of which are somewhat domain-specific (see Stylianou, this volume for a detailed discussion). Even a straightforward principle such as self-explanation is not consistently effective when implemented with MRs—learners may need to learn the discipline-specific representations and their unique conventions (e.g., Cartesian coordinate system, arrows in physics free body diagrams), and task interventions—i.e., instruction—needs to be customized to these. Furthermore, the most obvious task interventions, such as telling students to slow down animations, do not always have large effects. Other types of modifications such as animated cueing or using static diagrams to convey dynamic phenomena actually have larger effects. In addition, some task instruction appears to have effects on specific types of learning outcomes; self-explanation instruction—which includes fostering inferences—has effects more on inferential outcomes than on memory for facts.

A second insight from these task intervention studies is that effects vary across both dependent (i.e., learning outcome) variables and MR types. Whether to choose a task intervention or try to foster learning by designing the display differently might depend, for example, on whether the learner is using animation vs. a simulation. For inferential outcomes, learning from animation appears to be better fostered by design, whereas for games, self-explanation (especially pull-down self-explanation) appears to be a better way to achieve those ends.

A third insight concerns the paradox of testing for intervention x learner individual difference interactions: on the one hand, a seemingly ineffective intervention can be shown to be effective for subgroup(s) of learners. On the other hand, once researchers have found these interactions, the task intervention needs to be cautiously recommended only for the subgroup that benefited (e.g., drag and drop is better for high-knowledge learners). Adaptive learning systems with MRs have been developed and tested, but results are mostly reported in conference proceedings, which were not reviewed here.

## Conclusions/implications

**Implications for design teams.** Helping learners become better able to learn from MRs is not a simple, straightforward task that can be accomplished with a few common principles. Design of learning tasks and task interventions (i.e., task supports) needs to simultaneously take into account the learner characteristics—especially knowledge, reading comprehension, and deductive reasoning—the multimedia type, the specific representations and their conventions and other design features, and the desired learning outcome (factual, inferential, procedural, transfer). Supports for the steps in the learning process appear to have larger effects than other types of instruction such as cueing specific parts of a representation. More “active” strategies (e.g., drawing vs. filling in blanks) are not consistently better; their effectiveness depends on the fit to the task, person, and content in the learning environment. Designing collaborative MR activities seems to lead to less learning, despite the potential for other beneficial outcomes such as creativity or teamwork skills. Preliminary studies that reveal where learners face obstacles in certain tasks can help pinpoint exactly what task interventions should support. A formal, logical analysis of the task—called a task analysis—can also help identify what task interventions should support.

Research suggests many effective vehicles for delivering these interventions—through direct instruction by teachers, strategy cue cards, tutors, or embedded in the learning environment (e.g., via segmented worked examples with interspersed problems). In general, very complex multi-part strategy instruction is not recommended—it is less effective and less well taken up by learners (Bokosmaty et al., 2014)—whereas shorter, simpler suites of strategy instruction are recommended. In this sense, in this research we have overestimated learners and how quickly they can acquire new skills.

**Implications for researchers.** In many studies we reviewed, researchers collected individual difference data but never tested for interactions with task interventions. If these data are collected, it is wise to always test for interactions; this would then result in some possible cautions to teachers and other end users (e.g., best suited for undergraduate students, etc.). Patterns in the literature above might help researchers avoid unproductive studies (e.g., self-explanation in text and diagrams). Focused literature review in the multimedia type and dependent variable(s) of interest should also point in productive directions.

**Implications for teachers.** Implementing MR learning packages that try to change what learners do is a bigger challenge than just counting on design to lead to learning. After all, most representations are specific to a discipline, and no matter how well designed, students will need some instruction in how to use them, how to understand relations among different representations, and how to draw conclusions using them. On the other hand, these investments of time and effort can help learners become more independent and may be applicable to new learning situations (i.e., transfer). Learners benefit more when they get feedback on their use of new learning strategies, whether informally by observing learning, in feedback on their answers to questions posed during learning, or by other means. As noted above, simpler suites of strategy instruction appear to be more effective and more often actually practiced by learners, compared to extended, multi-part strategies. Solo work appears to lead to better learning than various types of collaboration. In addition, different strategies might be best for learning facts than for drawing conclusions, learning step-by-step procedures, or transferring skills to new contexts. Choosing instructional packages should take into account the desired outcome(s) and also the type of multimedia employed.

Our results point to a much more complex picture than perhaps has been conveyed previously about supporting learning from MRs. That complexity, though, reflects the realities of science, mathematics, and engineering content, as well as the complexities of human beings learning in social and material environments. Learning is not simple and straightforward, learning from MRs is not simple and straightforward, and supporting people in learning how to learn from MRs is not simple and straightforward.

**References**


Bodemer, D., & Faust, U. (2006). External and mental referencing of multiple representations. *Computers in Human Behavior, 22*(1), 27-42.

Bokosmaty, S., Sweller, J., & Kalyuga, S. (2015). Learning geometry problem solving by studying worked examples: Effects of learner guidance and expertise. *American Educational Research Journal, 52(*2), 307-333.

DeLeeuw, K. E., & Mayer, R. E. (2008). A comparison of three measures of cognitive load: Evidence for separable measures of intrinsic, extraneous, and germane load. *Journal of Educational Psychology, 100*(1), 223-234.

Duffy, M. C., & Azevedo, R. (2015). Motivation matters: Interactions between achievement goals and agent scaffolding for self-regulated learning within intelligent tutoring system. *Computers in Human Behavior, 52*, 338-348.

Höffler, T. N., & Leutner, D. (2011). The role of spatial ability in learning from instructional animations–Evidence for an ability-as-compensator hypothesis. *Computers in Human Behavior, 27*(1), 209-216.

Isberner, M., Richter, T., Maier, J., Knuth-Herzig, K., Horz, H., & Schnotz, W. (2013). Comprehending conflicting science-related texts: Graphs as plausibility cues. *Instructional Science, 41*(5), 849-872. doi:10.1007/s11251-012-9261-2

Johnson, A. M., Ozogul, G., & Reisslein, M. (2015). Supporting multimedia learning with visual signalling and animated pedagogical agent: moderating effects of prior knowledge. *Journal of Computer Assisted Learning*, *31*(2), 97-115.

Kastens, K. A., Pistolesi, L., & Passow, M. J. (2014). Analysis of spatial concepts, spatial skills and spatial representations in New York State regents Earth science examinations. *Journal of Geoscience Education*, *62*(2), 278-289.

LaDue, N. D., Libarkin, J. C., & Thomas, S. R. (2015). Visual representations on high school biology, chemistry, earth science, and physics assessments. *Journal of Science Education and Technology*, *24*(6), 818-834.

Mason, L., & Tornatora, M. C. (2016). Analogical encoding with and without instructions for comparison of scientific phenomena. *Educational Psychology, 36*(2), 391-412.

Mason, L., Pluchino, P., & Tornatora, M. C. (2015). Eye-movement modeling of integrative reading of an illustrated text: Effects on processing and learning. *Contemporary Educational Psychology, 41*, 172-187.

Mayer, R. E. (2014). Cognitive theory of multimedia learning. In R. E. Mayer, (Ed.), *The Cambridge handbook of multimedia learning* (pp. 43-71). NY, NY: Cambridge University Press.

Merchant, Z., Goetz, E. T., Keeney-Kennicutt, W., Kwok, O. M., Cifuentes, L., & Davis, T. J. (2012). The learner characteristics, features of desktop 3D virtual reality environments, and college chemistry instruction: A structural equation modeling analysis. *Computers & Education*, 59(2), 551-568. doi:10.1016/j.compedu.2012.02.004

Olympiou, G., & Zacharia, Z. C. (2012). Blending physical and virtual manipulatives: An effort to improve students' conceptual understanding through science laboratory experimentation. *Science Education*, *96*(1), 21-47.

Paas, F., & Sweller, J. (2014). Implications of cognitive load theory for multimedia learning. In R. E. Mayer, (Ed.), *The Cambridge handbook of multimedia learning* (pp. 27-42). NY, NY: Cambridge University Press.

Pachman, M., Sweller, J., & Kalyuga, S. (2013). Levels of knowledge and deliberate practice. *Journal of Experimental Psychology: Applied, 19*(2), 108-119.

Pachman, M., Sweller, J., & Kalyuga, S. (2014). Effectiveness of combining worked examples and deliberate practice for high school geometry. *Applied Cognitive Psychology, 28*(5), 685-692.

Shah, P., & Freedman, E. G. (2011). Bar and line graph comprehension: An interaction of top-down and bottom-up processes. *Topics in Cognitive Science*, *3*(3), 560-578.

Wang, T. H. (2011). Developing web-based assessment strategies for facilitating junior high school students to perform self-regulated learning in an e-learning environment. *Computers & Education, 57*(2), 1801-1812.

White, S., Chen, J., & Forsyth, B. (2010). Reading-related literacy activities of American adults: Time spent, task types, and cognitive skills used. *Journal of Literacy Research*, *42*(3), 276-307.

Yaman, M., Nerdel, C., & Bayrhuber, H. (2008). The effects of instructional support and learner interests when learning using computer simulations. *Computers & Education, 51*(4), 1784-1794.